Predictive Analysis and Root Cause Identification of Equipment Failures Using Event Log Patterns: A Focus on EUV/DUV Equipment

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***Abstract*—In the rapidly evolving field of semiconductor manufacturing, the productivity and reliability of advanced semiconductor equipment, especially Extreme Ultraviolet (EUV) and Deep Ultraviolet (DUV) lithography systems, are of paramount importance. This research introduces a cutting-edge methodology that employs the analysis of the rarity of event logs to preemptively identify potential failures and their root causes within such equipment. By establishing an optimized threshold that delineates the normal from the rare, this approach effectively flags those rare logs that exceed this threshold as indicators of potential failures. Subsequent analysis of these logs reveals the underlying mechanisms of failure, allowing for timely intervention. The application of this methodology to EUV/DUV equipment has demonstrated a significant increase in predictive accuracy, with a recall of 97.6%, and the potential to realize annual savings of nearly $2 million by reducing equipment downtime and maintenance costs.**

Keywords—Prediction, Breakdown, Failure symptom, Event log, Occurrence rarity, EUV, DUV

I. Introduction

As semiconductor manufacturing technology continues to advance, the demands on the performance and reliability of the equipment used in these processes similarly escalate. Despite significant advancements in manufacturing technologies, equipment failures remain an inevitable challenge, often due to a complex interplay of various factors or unpredictable equipment conditions. Previous studies have attempted to predict such failures by analyzing historical data on equipment performance [1]. However, these efforts frequently encountered limitations in accurately identifying the root causes of failures within the actual manufacturing environment [2,3]. While predicting the occurrence of a failure is crucial, understanding its root cause is essential for improving equipment productivity and reliability. This research posits that a detailed analysis of equipment event logs, which record system events, alarms, and errors, can offer valuable insights into potential failures, thereby enhancing operational efficiency [4].

The primary objectives within a production line include the meticulous monitoring of equipment conditions to anticipate and mitigate unexpected failures, and minimizing equipment downtime following a failure. Achieving these objectives necessitates the rapid identification of failure symptoms and the development of preemptive solutions to facilitate quick equipment recovery. Given the sheer volume of logs produced by semiconductor manufacturing equipment, which can range from hundreds to thousands per hour, there is a pressing need for a method that allows field engineers to accurately predict and analyze potential failures without being overwhelmed by data.

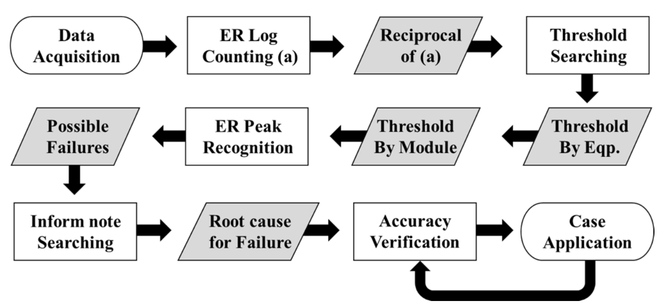

Fig. 1. The overall process of methodology

In response to this need, this study has developed a novel method that utilizes the inverse frequency of occurrence of equipment logs as an indicator of their rarity (Fig. 1). Error Report (ER) logs, which encapsulate system events, alarms, and errors, are critical for identifying equipment abnormalities [5]. These logs are among the first pieces of information that engineers consult when diagnosing a failure [6]. Given the varying frequency of each log type, their rarity can serve as a strong indicator of potential issues. This study proposes a methodology where logs that are infrequently generated are

2024 35th Annual SEMI Advanced Semiconductor Manufacturing Conference (ASMC) | 979-8-3503-8455-0/24/$31.00 ©2024 IEEE | DOI: 10.1109/ASMC61125.2024.10545492

considered more indicative of potential failures than those that occur more frequently. By plotting these inverse frequencies, the method can identify potential failure triggers that exceed a predetermined threshold, which is tailored to the specific equipment being monitored.

II. METHOD

The methodology hinges on the analysis of ER logs, which include system events, alarms, and errors, to detect changes in equipment condition and identify abnormalities [7]. The frequency of occurrence of each log type varies significantly, from normal logs that occur as part of routine operations to rare logs that may only appear once or twice a year. This variation allows for the utilization of the reciprocal value of each ER log's frequency as a measure of its rarity (Fig. 2). Logs that occur frequently, sometimes thousands of times per day, are often not indicative of equipment health issues and thus have a lower correlation with potential failures. In contrast, logs that rarely occur under normal equipment conditions are considered more significant indicators of potential problems.

ER Log ※ "Header" – "number"	Number of occurrences (a)	Reciprocal of (a)
AB-1212	8B	***1.2×10^{-10}***
CD-1234	700M	***1.4×10^{-9}***
EF-1004	50M	***2.0×10^{-8}***
ZX-4545	10M	***1.0×10^{-8}***
XY-6789	5M	***2.0×10^{-7}***
…	…	***…***
YZ-1357	1	***1***
YZ-2468	1	***1***

Fig. 2. An example of one-year ER logs with each number of occurrence and its reciprocal value

To establish a threshold for identifying these rare logs, the reciprocal value of the frequency of occurrence of each log, referred to as the 'Occurrence Rarity,' is used as a key metric. By plotting this metric, it is possible to identify logs that exceed a certain threshold value, depicted as a red line in the methodology's visual representations. This threshold is dynamically adjusted according to the time zone and specific conditions of the equipment under analysis to achieve the highest model accuracy (Fig. 3).

A crucial aspect of the methodology is the identification of periods where the reciprocal value of the occurrence frequency of ER logs increases sharply, indicating an imminent failure. Through analysis, it was found that for EUV/DUV equipment, the most significant increase in rare log occurrences often happens approximately 15 minutes before a failure (Fig. 4). This finding suggests that setting an appropriate threshold value and monitoring for logs that exceed this threshold during the 15-minute pre-failure window can effectively signal impending failures.

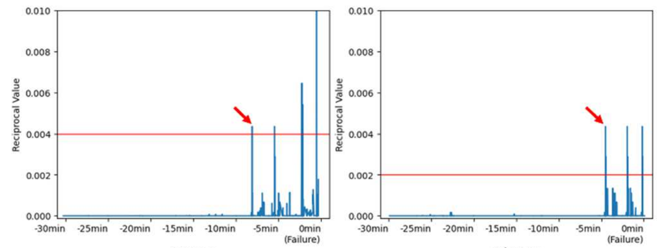

Fig. 3. Threshold change for each time zone of the target equipment

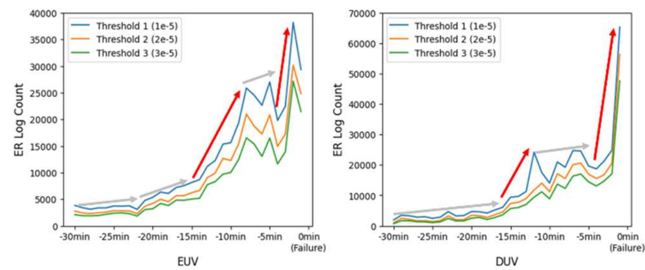

Fig. 4. Section where the incidence of ER log above the threshold value soars (-15min ~ Failure)

Moreover, the format of the ER log codes, which include a header indicating the hardware or software module, facilitates the identification of the specific module where each log occurred. This capability enables a more focused analysis of module-specific conditions, conserving resources and allowing for the preparation of targeted solutions in the event of a failure. By applying this method, it is possible to track the propagation of abnormalities from one component or module to others, enhancing the understanding of failure dynamics within the equipment.

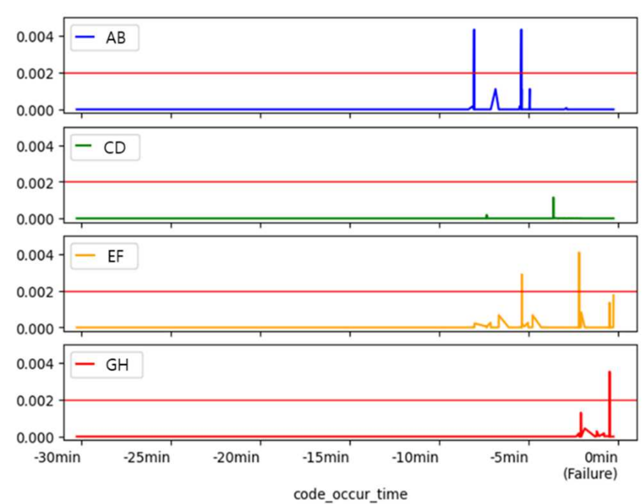

Fig. 5. Detection process of abnormality by module until failure occurs

The equipment in the left plot of Fig. 3 can be separated into modules, and it can be shown in Fig. 5. As a result of testing by lowering the threshold to 0.004, peaks were detected in various modules, and peaks occurred sequentially for each module. It will be possible to understand the process of propagating abnormality of a component to other component or even entire equipment. Therefore, utilizing this methodology, preemptive measures can be taken, like manually removing the wafer, as supported by historical failure data.

For example, if more peaks are detected in the 'AB' module than other modules, this module means that there are many factors that can cause failure. In addition, since peaks occurred sequentially in the rest of the modules after peaks occurred in the 'AB' module, there may be sequential effects over time. If the reciprocal value of incidence of ER log in a specific module can be related to failure or predict failure, this relation can become clearer through machine learning for solving these problems. To this end, based on the previously set time (15 minutes before failure), it was tagged as 'Bad' period until 15 minutes before failure and 'Good' period from 30 minutes before failure to 15 minutes before failure (Fig. 6). The meaning of 'Good' period refers to a period in which the equipment is in a normal state, in which no signs of failure can be found, and 'Bad' period refers to a period in which signs of failure can be found due to the occurrence of ER Log.

	Tag	AB	CD	EF	GH	...	WX	YZ
Case 1	Good	0	0	0	1.26E-06	...	0	0
	Bad	2.12E-06	1.01E-06	1.08E-05	1.55E-06	...	0	0
Case 2	Good	0	0	0	0	...	0	0
	Bad	0	1.01E-06	2.29E-04	0	...	0	0
Case 3	Good	0	0	0	8.91E-05	...	0	0
	Bad	0	1.01E-06	1.08E-05	1.55E-06	...	0	0
Case 4	Good	0	1.01E-06	1.08E-05	1.55E-06	...	3.22E-05	0
	Bad	0	0	1.08E-05	0	...	0	0
Case 5	Good	0	0	0	4.80E-04	...	0	0
	Bad	2.12E-06	1.01E-06	3.22E-05	1.55E-06	...	0	8.33E-02

Fig. 6. Maximum reciprocal value of incidence of ER log for each module for training

The above data set can be split into train and test data to confirm the accuracy of the failure prediction of model. In addition, the importance of each module can be calculated using a decision tree-based machine learning method such as Random Forest [9]. After checking the failure history in the engineering history note, it will be possible to verify the applicability of the field by comparing it with the failure cause derived from the model.

III. CASE STUDY AND RESULT

The methodology was rigorously tested through a case study involving EUV equipment, a critical component in the production of ultra-fine semiconductor devices [10]. The study analyzed approximately 2,040 instances of maintenance history for EUV/DUV equipment over a 12-month period. During this time, a wide range of ER logs were examined, from those occurring over 100 million times a year to those with only a single occurrence. This vast disparity in log occurrence frequencies underscores the challenge of identifying meaningful indicators of equipment health.

Among the ER logs analyzed, approximately 5,000 were identified as occurring less than 10 times a year in the EUV/DUV equipment, categorizing them as highly unique and significant. These rare logs are more likely to be associated with specific, abnormal conditions, potentially indicating equipment failures or abnormalities. The study's analysis of these logs revealed a clear distinction between frequently occurring logs, which are likely benign, and rare logs, which warrant further investigation due to their potential link to equipment issues. Here, the special situation may be a failure or equipment abnormality. About 2,300 ER logs of EUV equipment occurred less than 10 times a year, and the distribution is as follows (Fig. 7).

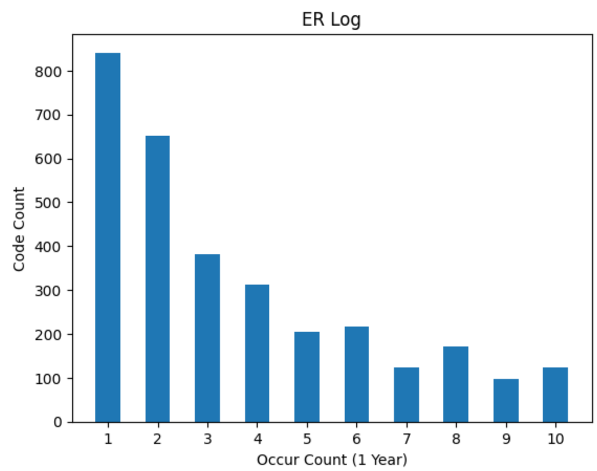

Fig.7. The count of ER logs of EUV equipment per year (2022)

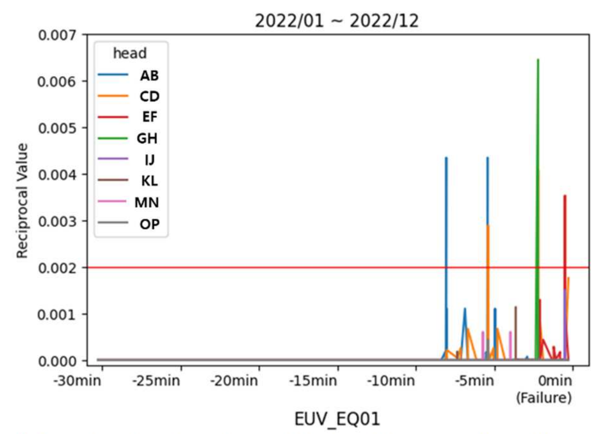

Fig. 8. Peak detection above threshold before failure for each module

To quantify the impact of these logs on equipment health, the 'Reciprocal Value of Incident of ER Log' was developed as an evaluation metric. This metric highlights the stark contrast in occurrence frequencies among different logs, with some differing by factors of up to 100 million. In practical applications, the methodology enabled the identification of significant peaks above the threshold value as early as 8 minutes before a failure, providing a crucial window for intervention (Fig. 8).

A specific case highlighted in the study involved the "AB" module, where an initial failure was detected due to a wafer location read error (Fig. 9). This incident was followed by subsequent failures in the "CD" and "EF" modules, ultimately leading to a complete equipment failure. The study's Random Forest model identified the "CD" module as the primary contributor to the failure, illustrating the methodology's ability to pinpoint specific areas of concern.

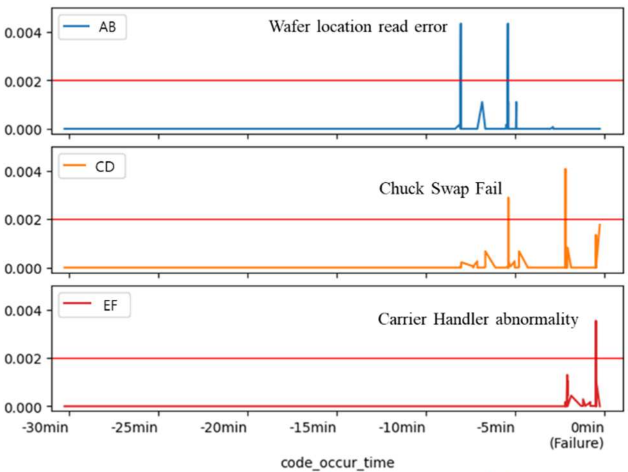

Fig. 9. Detection process of abnormality by module until failure occurs

Furthermore, the sequential occurrence of ER logs exceeding the threshold in various modules provided a clear timeline of events leading up to a maintenance event, identified by the failure code "CD-815C" (Fig. 10). This sequence allowed engineers to follow the progression of issues across modules, culminating in a comprehensive understanding of the failure and the subsequent actions taken for recovery. By comparing these findings with historical failure data, the study confirmed the methodology's applicability and consistency in real-world scenarios.

ER Log	Occurrence time	Description	Value
AB-3183	2022-11-XX HH:00:00	Wafer wedge not enough	***0.0043***
AB-3180	2022-11-XX HH:00:00	Linked error	***0.0043***
AB-3000	2022-11-XX HH:03:00	Linked error	***0.0022***
CD-815C	2022-11-XX HH:03:00	Chuck Swap failed.	***0.0029***
…	…	…	…
EF-2324	2022-11-XX HH:07:00	CHUCK: function exception	***0.0035***
EF-3724	2022-11-XX HH:08:00	Carrier Handler error	***0.0025***
LO-9999	2022-11-XX HH:09:00	Automatic Recovery failed **(FAILURE)**	***1***

Fig. 10. ER Log path of the actual case (2022-11-XX)

Of course, this methodology can be applied to the FAB as a regular system. If a value above threshold occurs, the model automatically recognizes and sends an alarm to the equipment, and the engineer can quickly check and analyze the cause of the preliminary failure through this alarm to prevent potential BM (Break Maintenance) or respond with an optimized solution in case of BM.

IV. Conclusion

The methodology introduced in this study marks a significant leap forward in the realm of semiconductor manufacturing, with a particular emphasis on the predictive maintenance of EUV and DUV lithography systems. By concentrating on the rare occurrences within event logs and their associations with potential equipment failures, the approach provides a sophisticated and highly effective means for early failure detection. Boasting impressive recall rates—98.8% for EUV and 97.6% for DUV systems—the methodology demonstrates not only its efficacy in reducing downtime and maintenance costs but also its adeptness in pinpointing module-specific causes of failures, thereby enhancing targeted interventions (Fig. 11).

		Model		
		Abnormal state	Steady state	**Recall**
Real	Abnormal state	1220	30	***97.6%***
	Steady state	246	1004	
	Precision	*83.2%*		***89.0%***
				Accuracy

Fig. 11. Confusion matrix of model for DUV

The methodology developed in this study is an original methodology that has never been applied before, but it is very simple and powerful. In addition, by tracking the path of the ER log rather than simply predicting a failure, it is possible to identify the main causes of failure such as errors in a specific module and related influencing factors. It can also be used to provide a verified solution by checking the failure histories in inform note similar to the target failure. Above all, the accuracy of failure prediction is very high, and it would be a great competitiveness of this methodology to be able to determine the cause of failure for each module. However, the reason why failure can be predicted with such high accuracy is the high quality and accuracy of logs generated in this equipment. It may be difficult to apply the methodology of this study in equipment without logs that record the status of each module so accurately.

The success of this approach opens up avenues for further refinement and improvement. The integration of advanced machine learning techniques, such as Deep Learning and Long Short-Term Memory (LSTM) networks, promises to elevate the predictive accuracy and consistency of the methodology. Moreover, the incorporation of Large Language Models (LLMs) for understanding the context of equipment logs, combined with techniques like fine-tuning, Retrieval-Augmented Generation (RAG), and Chain of Thought (COT) for enhanced reasoning capabilities, could revolutionize the way we interpret and act on the data generated by semiconductor manufacturing equipment.

Additionally, the adoption of Knowledge Graphs, enriched with a lithography-specific knowledge base, presents a promising avenue to further refine the process of root cause analysis. By structuring and linking relevant information, Knowledge Graphs can provide a more nuanced understanding of the intricate relationships between different components and processes within lithography systems. This structured approach to data can significantly aid in the swift identification of underlying issues, leading to more informed decision-making and efficient problem resolution.

As the semiconductor industry continues to advance, embracing these innovative methodologies and technologies will be crucial for maintaining the high levels of reliability and efficiency required in modern semiconductor manufacturing processes. The ongoing development and integration of such cutting-edge tools and techniques will undoubtedly play a pivotal role in shaping the future of equipment maintenance strategies within the industry.

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